Visualizing the Periods of Stock Prices Using Non-Harmonic Analysis of the NASDAQ Composite Index Since 1985

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Abstract: The prediction of stock prices is studied extensively, because of the demand from private investors and financial institutions. However, long-term prediction is difficult due to the large number of factors that affect the real market. Previous research has focused on the fluctuation patterns and fluctuation periodicity of stock prices. We have likewise focused on the periodicity of stock prices. We have used a new high-resolution frequency analysis (non-harmonic analysis) method can solve the previous problem of the frequency resolution being low. As a consequence, we have succeeded in visualizing the various periodicities of stock prices. The periodicity fluctuates gently in many periods, but we have confirmed that it fluctuated violently in periods when a sudden event occurred. We expect that this experimental result in combination with previous research will help increase predictive accuracy and will aid long-term prediction.

Keywords: Stock price prediction, Stock market, Fourier transform, Non-harmonic analysis, Periodicity of stock prices.

1. INTRODUCTION

Economic time series prediction is studied extensively. In particular, stock price prediction is demanded by private investors and financial institutions. Stock price fluctuations are generally considered by economic and finance theory on the basis of the efficient market hypothesis. E. F. Fama (Fama, 1970) published a thesis that the fluctuation pattern of stock prices does not exist and, rather, they follow a random walk.

However, the random walk theory has now been negated by the study of A. W. Lo, *et al.* (Lo and Mackinlaye, 1988). Some typical examples are cited that follow business cycle theory and Elliott wave theory (Schumpeter, 1939; Elliott, 1994). These theories claim that a pattern and cycle do exist in stock price fluctuations.

In general, time series signals have a plural frequency. Assuming that an economic time series, such as stock prices, is a time series signal, it is supposed that it will consist of a plural frequency. Our purpose is to analyze and visualize the frequency and cycle that constitute the stock price more precisely.

To data, various techniques to predict stock price fluctuations have been proposed. Representative techniques include Artificial Intelligence Modeling, Statistical Analysis, and Signal Analysis. Most of these techniques are used to focus on the cycle, i.e. the pattern or trend of stock prices.

Artificial Intelligence Modeling includes The agent model and Artificial Neural Networks (e.g., Shimokawa, Misawa and Watanabe, 2006; Guresen, Kayakutlu and Daim, 2011). The agent model deploys many kinds of agent that imitate human beings in a virtual society on a computer and simulate the movement of the whole system by letting local interactions between agents occur (Sakai and Kawai, 2006). An agent model can model a process of information transmission and investigate what influence it has on market price formation and predictive possibilities. However, in an agent model, setting parameters to completely account for all real markets is impossible. Therefore, this reduces the predictive accuracy.

The neural network is a learning technique that has imitated the combination of neurons in the human brain mathematically. It can obtain useful solution with little calculation time for problems that have multidimensional data and where linear separating is impossible. It is being used in various fields (Mcculloch and Pitts, 1943; Rumelhart, McClelland and PDP Research Group, 1986), for example, pattern recognition and data mining. It is also used in the prediction of stock price fluctuations; it predicts future stock prices by learning the pattern of stock prices and economic indicators. The weakness of using an artificial neural network to predict stock prices is that if

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it uses past data when predicting the stock price of the day, the error would be large. Therefore, it is considered to be very difficult to predict stock prices in the long term in this way.

Statistical Analysis often includes using the normal distribution. It is widely known that random phenomena approximately obey the normal distribution, and it has been suggested to use this for stock price prediction (Yanagawa, 1990). In stock price prediction, the normal distribution had mainly been used with a focus on the rate of return. However, the fact that the rate of return does not actually obey the normal distribution has been well publicized (Greenspan, 1997). Yet, a large number of financial institutions assume normality of the rate of return and this has been widely used for tendency analysis.

Relative to other distributions the normal distribution is extremely easy to handle mathematically (Danielsson and Morimoto, 2000). However, this makes a model from an overall statistical value; therefore, the model becomes imprecise and the predictive accuracy drops.

Signal analysis includes the linear regression mode, the ARMA model, and the Fourier transform. The linear regression model is a model that express trends clearly by making complicated data linear. This model makes predictions of stock prices using past data on prices and explanatory variables. Because this model gives an output of an observation level including an error, it is not suitable for long-term predictions. The ARMA model consists of the AR model and the MA model; the AR model takes a linear shape from the sum of an input value and the previous value, in addition the MA model takes a linear shape from the sum of the output value of the AR model and the previous value (Kamiyama, Furuya, Sekiguchi and Tanaka, 1996). This model is generally used after removing distortion from the mean value because modeling non-steady signals, such as stock prices, is difficult. The Fourier transform is generally used to analyze the signal period, like a Discrete Fourier Transform, and the Fourier transform is used to analyze the period of the fluctuations in stock prices. However, this technique is not often used for economic time series predictions, because the accuracy of the analysis may decrease with the analysis window length.

As mentioned above, stock price prediction techniques include Artificial Intelligence Modeling, Statistical Analysis, and Signal Analysis. However, these techniques each have their problems. In the artificial intelligence modeling, the predictive period is short. In the statistical analysis, the mode becomes imprecise and the predictive accuracy deteriorates due to the model being made from an overall statistical value. In the signal analysis, the frequency of the resolving power is low, and the predictive accuracy declines with the analysis window length. These problems mean that these techniques cannot estimate the cycle or pattern of stock prices exactly.

To solve these problems, we have recently developed a high-resolution frequency analytival method NHA (Non-Harmonic Analysis) that is not a affected by the analysis window length. NHA can highly accurately estimate the cycle of a signal, including elements with a long period, like stock price fluctuations. Furthermore, the estimation method enables long-term prediction by composing the elements of a period (e.g., Hirobayashi 2008; Ichinose and Hirobayashi, 2012). NHA can solve the problem that the frequency resolving power is low in signal analysis, because it is almost entirely independent of the analysis window length. M. Cheseny (Chesney, Reshetar and Karaman, 2011) analyzed the effect that a sudden event relecant to stock price fluctuations, such as terrorism had on stock prices. With regard to the predictive technique that the authors developed, its predictive accuracy was worsened by sudden changes to stock prices, because the case of sudden events had not been estimated. Therefore, we consider that analysis and visualization of the periods in which stock prices are composed is important for making predictions for the long term that are highly accurate.

In this paper, we visualize and analyze the periods of fluctuation in time series data using NHA.

We believe that confirming the period of fluctuation impact on stock prices can improve the accuracy of their predictions.

2. METHOD

2.1. Characteristics of the Fourier Transform and Overview of NHA

In general, the Discrete Fourier Transform (DFT) is used to analyze a signal's period and it is well known to be effective. However, the accuracy of DFT analysis is low, because the analytical accuracy depends on the window length. A discrete spectrum X of the discrete time signal $x(n)$ of length N can be expressed as:

$$X(k) = \frac{1}{N}\sum_{n=0}^{N-1} x(n) e^{\frac{-j2\pi kn}{N}} \quad (k = 0,1,2, \ ,N-1) \tag{1}$$

When the sampling period is Δt and the original signal $x(n)$ has a period of $N\Delta t / k$, $X(k)$ can accurately reflect the spectral structure. If a period other than $N\Delta t / k$ appears in $x(n), X(k)$ is expressed by the combination of $N\Delta t / k$ from several frequency components and $X(k)$ is not accurately reflected in the spectral structure.

To increase the frequency resolution, the value of N is generally increased. If the frequency is accompanied by a temporal fluctuation, however, the average period is extracted and the analytical accuracy deteriorates as N is increased. Some techniques use an analysis window function for $x(n)$ in preprocess; however, this does not improve the apparent frequency resolution.

To increase the frequency resolution, the Multi-Window Fourier Transform (MWFT) and Generalized Harmonic Analysis (GHA) were proposed. MWFT employs an apparent increase in the frequency resolution (e.g., Onishi *et al.,* 1997; Fukuda *et al.,* 1996), while GHA employs an analysis with windows of variable length (Terada *et al.,* 1994; Wiener, 1958). However, these frequency analysis techniques have not generally been used to predict economic time series, because their frequency resolution is not high enough for such predictions and their accuracy may deteriorate through being affected by the analysis window length. We have experimented with extrapolating the front and tail signals using data from the NASDAQ, to prove that there is a possibility for this analysis method to actually be used for economic forecasts. Since the Fourier coefficient is estimated by solving a nonlinear equation, NHA enables the frequency and its associated parameters to be estimated accurately without being much influenced by the length of the analysis window.

To minimize the sum of squared differences between the object signal and the sinusoidal model signal, the frequency, $\hat{f}$, amplitude, $\hat{A}$, and initial phase, $\hat{\varphi}$, are calculated as follows:

$$F(\hat{A},\hat{f},\hat{\varphi}) = \frac{1}{N}\sum_{n=0}^{N-1}\left\{x(n) - \hat{A}\cos\left(2\pi\frac{\hat{f}}{f_s}n + \hat{\varphi}\right)\right\}^2 \tag{2}$$

where N is the frame length and f_s is the sampling frequency $(f_s = 1/\Delta t)$. E. B. George and M. J. Smith attempted to introduce the signal parameter, A, and the initial phase, φ, by applying the method of least mean squares to the difference between the analyzed signal and the modulated harmonic sinusoidal wave (E. B. George and M. J. Smith, 1992, 1997). However, this method is strongly dependent on the analysis window length and it is difficult to apply to the analysis of signals that don't have a simple frequency harmonic structure, since frequencies dependent on the window length are used for the group of detection frequencies, as in DFT. In other words, small frequency changes cannot be detected. By focusing on solving a nonlinear equation, we have applied the nonlinear equation process to Eqn. (2) to calculate the optimal frequency, f, as well as the optimal parameter amplitude, A, and initial phase, φ.

As a result, NHA is not much influenced by the analysis window length and it has been shown to determine periods to an accuracy of at least 10^4 to 10^{10} times higher than conventional analytical methods. Accordingly, NHA is compatible with time resolution and frequency resolution.

The result of our analysis of the signal sine wave using general DFT and NHA are shown in Figures **1** and **2**, where (a) is the original signal, (b) is the frequency element with the largest DFT estimate signal amplitude. (c) is the frequency element with the largest NHA estimate signal amplitude. When the period of the signal is shorter than the length of the analysis window, such as in Figure **1a**, DFT analyzes 0.8 periods for every 1.0 period as a share of the nearest integer period, as in Figure **1b**. Similarly, with a period of the signal that is shorter than the analysis window length, such as in Figure **2a**, DFT analyzes 2.3 periods for every 2.0 periods as a share of the nearest integer period, as in Figure **2b**. However, comparing Figures **1a** and **1c**, we can see that an accurate analysis is obtained with NHA, because NHA is not affected by the analysis window length.This result is similar to that shown in Figures **2a** and **2c**. That is, comparing a characteristic, such as the analysis window length, that does not become multiple in the period of a signal targeted for analysis, DFT cannot identify a period correctly, however, NHA does not depend on the analysis window length and can analyze a period. Therefore, it may be said that NHA has high analysis precision. On the other hand, the general method to improve the resolving power in DFT lengthens the analysis window. However, when the frequency is accompanied by a time change, the precision of this method of analysis is decreased, because an average

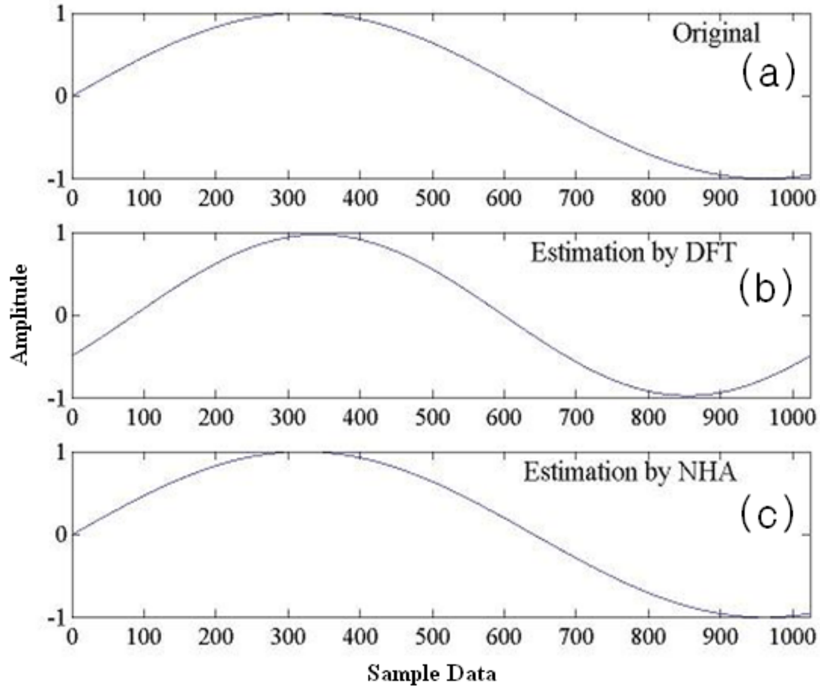

Figure 1: Estimation accuracy of single sinusoid (period of 0.8).

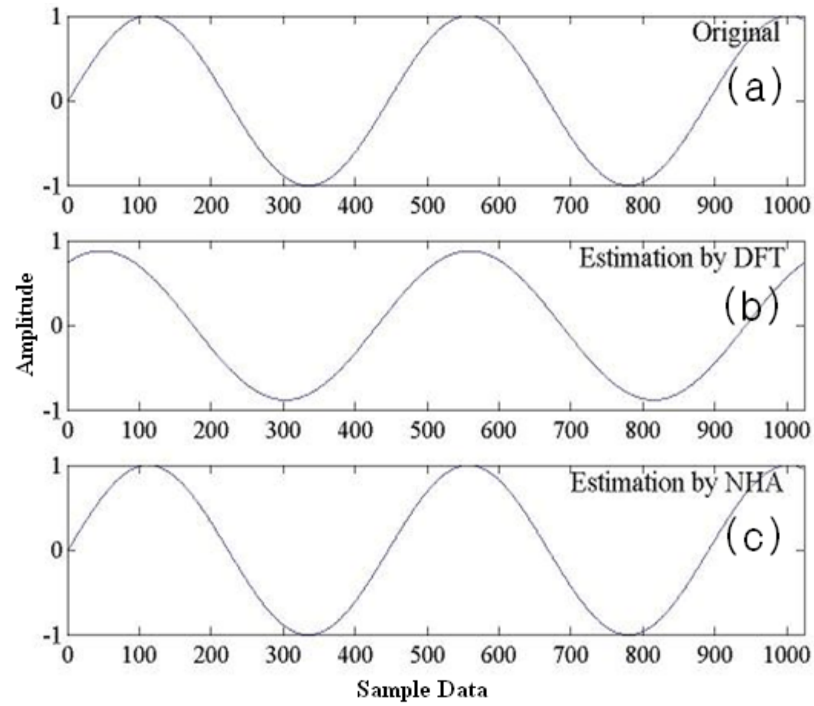

Figure 2: Estimation accuracy of single sinusoid (period of 2.3).

period is extracted. Under NHA, the analysis precision does not decrease, because it can deal with an element with high resolving power in a period, even if it is analyzed in a short window length. For more details about NHA further, please refer to the following paper (Yoshizawa, Hirobayashi and Misawa, 2011; Ichinose, 2012; Xu Cao, *et al.,* 2012; Uchida, *et al.,* 2013).

2.2. Periodic Factors Regarding the Stock Prices

The relationship of the stock price to its period cannot be confirmed by real stock price movements. However, various periods exist in everyday life, such as one week, one month, and one year. The period relevant to stock prices is considered to relate to factors such as the transition of a pay day, the season, and the time for the settlement of accounts.

Research regarding stock prices' period pays attention to various factors and the announcement of them. By way of example, there is an article that statistically considers the day of the week and the rate of return of the Greek Stock Exchange (Kenourgios and Samitas, 2008). From their results, the authrors found that Tuesday showed the smallest profit and Friday largest. Furthermore, there was a paper that published a wavelet transform and neural network integrated system, it divided stock prices into those with high frequency and low frequency, and then studied the increase in predictive accuracy from removing the low frequency data (Wang, Wang, Zhang and Guo, 2011).

Likewise, Elliott wave theory also focuses on the periodicity of stock prices. Elliott wave theory is a theory of the law of the movement of the market average price, which was proposed in 1934 by R.N Elliott. This theory defines the market average price as being comprised of eight waves, five rising waves and three falling waves.

Elliott wave theory was established for the present time by A. J. Frost and R. R. Prechter (Frost and Prechter, 1985). They classified the periodic wave in the ninth class in order to determine the basic concept for this theory. These periodic waves belong to various categories, which range from long periods of several centuries to short periods of several minutes, as shown in Table **1**. Moreover, according to this theory, the number of waves constituting stock prices stems from the Fibonacci series, which is seen in various context in the natural world.

Table 1: A Period's Classification in Elliott Wave Theory

Cycle Grade	Cycle Length
Grand Super Cycle	More than 100 years
Super Cycle	From 1 years to 70 years
Primary	From several months to 2 years
Intermediate	From several weeks to a few months
Minor	A few weeks
Minute	A few days
Minuette	A few hour
Subminuetet	A few minutes

In order to estimate the next term of a stock prices under Elliott wave theory, it is important to know the current position of waves in the ninth class. This theory has defined the fluctuation regularity of the basic eight waves. Accordingly, if we can know the current position of stock prices in the ninth class, then estimating the next term of the stock prices might become easy to do.

As suggested by these papers, focusing on the period of stock prices may allow us to find the stock prices fluctuation factor. If the fluctuation factor can be found, this leads to the possibility of predicting stock prices. In this paper, we visualize the period of stock prices and show how it exists.

In this experiment, using a characteristic of NHA, we confirm that how the period element is changing is determined by the window length. As a result that we actually predict the stock prices using NHA, we also can confirm which periods have a large predictive residual error and which a small predictive residual error [12, 13]. We have conjectured that both the accident and war that we consider happened in the period that has the large predictive residual error. However, when we consider the influences on the movement of real stock prices we cannot determine the factors impacting them only from their up and down movements, so we do not know what is affecting stock prices. Therefore, we propose a system to visualize the periods of stock prices fluctuations. Shown in Figures **3**, **4** and **5**, the periods of the fluctuations in stock prices is visualized using NHA, and we can confirm the price ratio in each periods.

In this paper, we use price data from approximately 25 years of the NASDAQ, from 1984 to 2010. We set the analysis window length to 1 and 2 years; we use these lengths because NHA cannot analyze too long a period as smoothing of the time resolving power would occur NHA also cannot analyze too short a period, because then an error occurs too easily in the long element. When we use it for testing, we suppose the window length of one year to be 256 days. This supposition defines a year as approximately all days of the year, year except Saturdays, Sundays, and National holidays, when stock trading is not carried out. Therefore, the window length of two years is 512 days. Moreover, we have focused on two differentelement patterns in the long period and short periods.The long period element is the longest period and the short period element is the periods that compose the stock prices, except for the long period element.

3. CHARACTERISTICS OF THE LONG AND SHORT PERIOD ELEMENTS IN THE STOCK PRICES

This section gives the results from analyzing the NASDAQ Composite Index using NHA. Figure **3** is an

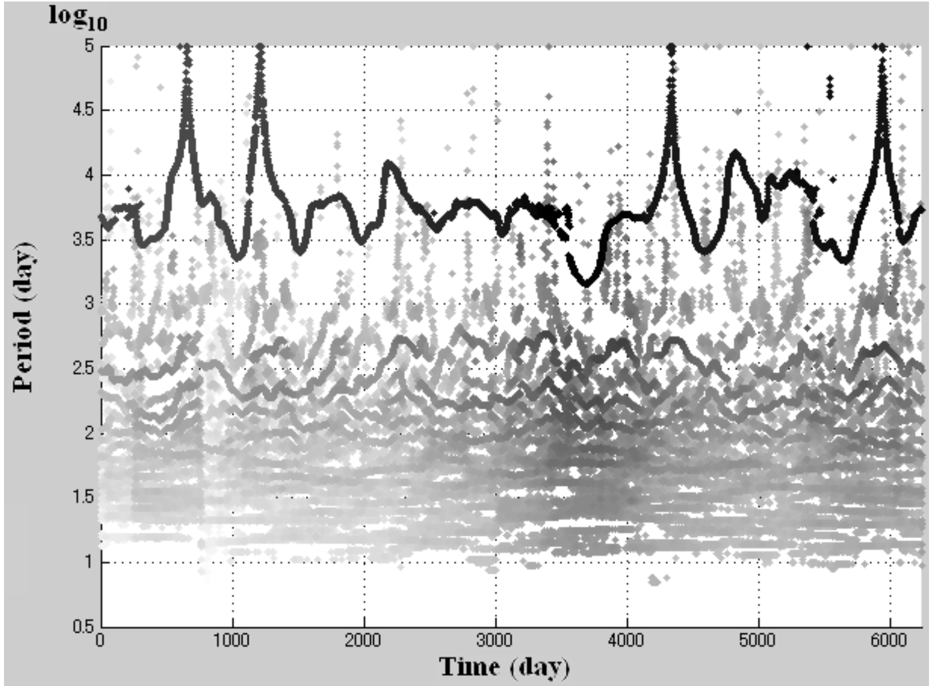

Figure 3: Period element for approximately 24 years.

actual result from our visualization of NASDAQ price data for 24 years. The X-axis of the figure represents the days of trading, while the Y-axis shows the period length, expressed as a logarithm. The deepness of the line represents the price ratio in each period, the deeper the line, the higher the prices ratio. From the figure we can confirm that stock prices are comprised of the wave of the period, which determines the various ways they behave. We can also confirm that the periods tend to infinity at four points in the long period element and that the price ratio changes in the short period elements.

In our analysis of the 24 years the long period element fluctuates gently, ranging from approximately 1,000 days to 10,000 days in many parts, as is shown in Figure **4**. In other words, we find that the long period element constituting the stock prices has a period ranging from approximately 4 years to 40 years. This

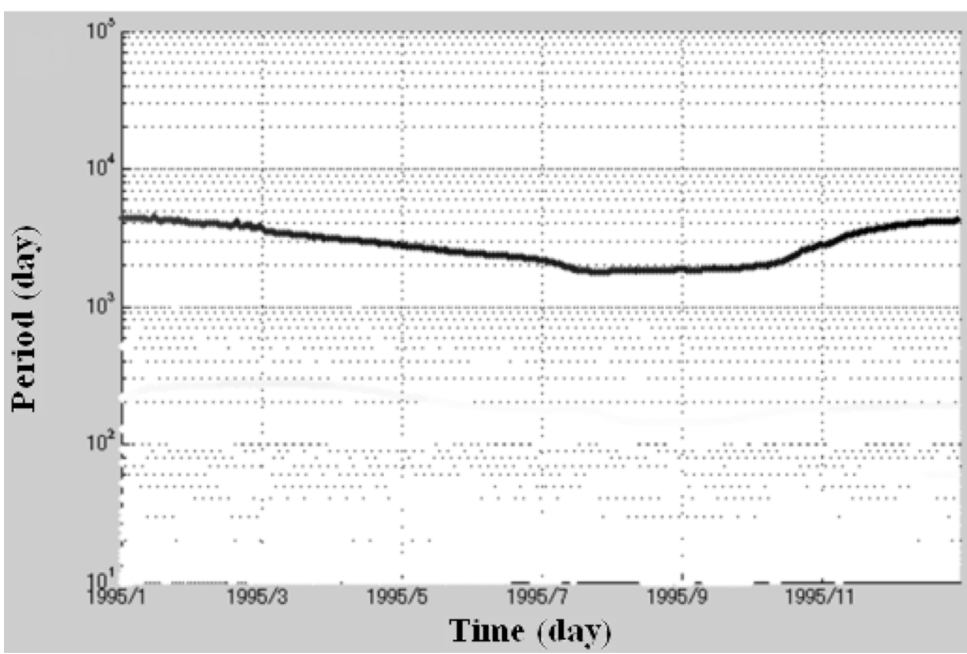

Figure 4: The longest period element of the stock prices in 1995.

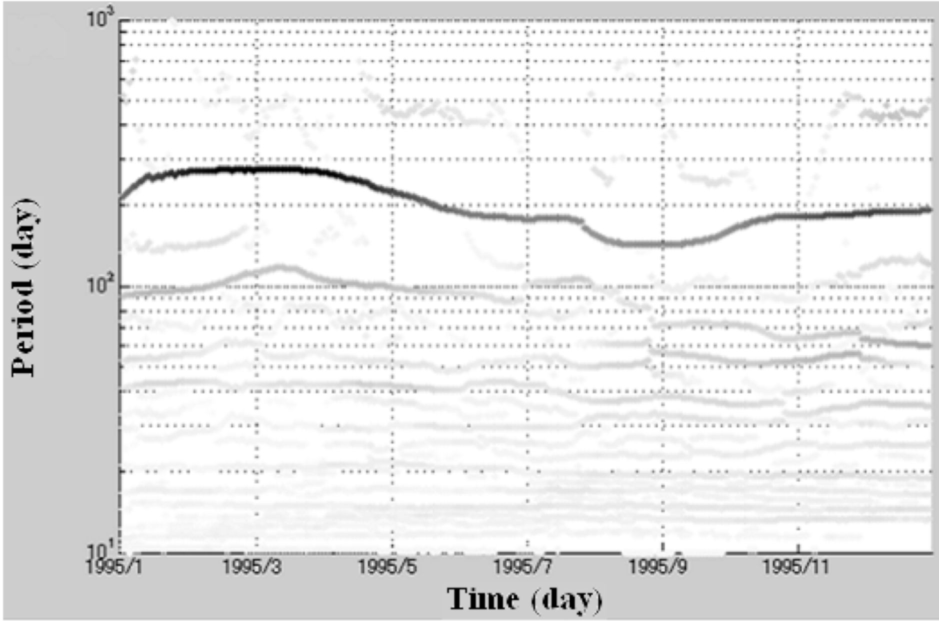

Figure 5: The shortest period element of the stock prices in 1995.

long period element accounts for approximately 80% of the constitution of the stock price ratio. For example, if on one day the stock price was 1000 yen, then the long period element has the a price of 800 yen. Accordingly, one could say that 80% of stock prices changes are fluctuations due to the influence of the long period element. Therefore, it may be said that this element is the most important factor to analyze.

The short period elements fluctuate gently in a similar ways to the long period element as shown in Figure **5**. The longer period tends to constitute a large proportion of the stock price ratio, as the length of the periods is shorter the amount of the price ratio they constitute is smaller. The short period elements account for approximately 20% of the constitution of the stock price ratio which is clearly smaller than for the long period element. However, we can confirm that its fluctuation does constitute prices to an extent, and we can say that it is an important factor to analyze

4. THE RELATIONSHIP BETWEEN EVENTS AND THE PERIODICITY OF STOCK PRICES

As stated in subsection 3.2, the long and short periods drew a slow linear shape together over the 24 years and we confirmed the period in which a large change is seen in the stock price cycle. This section consider the case of visualizing the stock price cycle in a period when an event which has a large influence on stock prices occurres. In particular, periods in which the stock prices experience a large change and where there is an influential phenomenon nearby include Black Monday, the Worldcom case, and the Lehman Shock. We show the result of our analysis of an approximate 2 year time period including the period when the event occurred, for each case. In the Worldcom case, because the event included the Sept.11 attack and the Enron case, we gives results of analysis for a period including all the phenomenona. We can see the change in real stock during the period when it is simultaneously analyzed for a comparison index. The red line in each figure shows the point in time when each phenomenon, influencing the stock prices, caused.

4.1. Black Monday

In finance, Black Monday refers to Monday October 19, 1987, when stock markets around the world crashed, losing huge value in a very short time. It was a significant event but, through policy cooperation between countries, it ended without causing a panic. When we look at the stock price fluctuations in Figure **6**, it reveals that the price suddenly falls on October 19. The results of our analysis used 2 years of data from January, 1987, to consider the case from before and after.

Considering the results of our analysis of the long period element with a window length of 256 days, as in Figure **7**, the phenomenon of a period tending to infinity is confirmed by the case of February 1988. Likewise, the period approximately 1000 days after the phenomenon also tended to infinity, however, we can confirm that the period increases until approximately

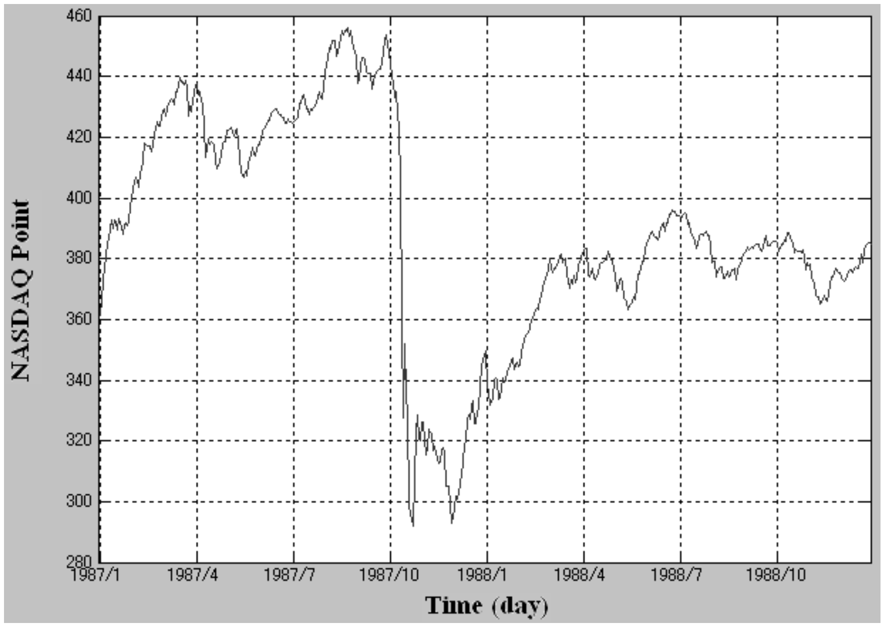

Figure 6: 2 years of the NASDAQ composite, from January 1, 1987 (including Black Monday).

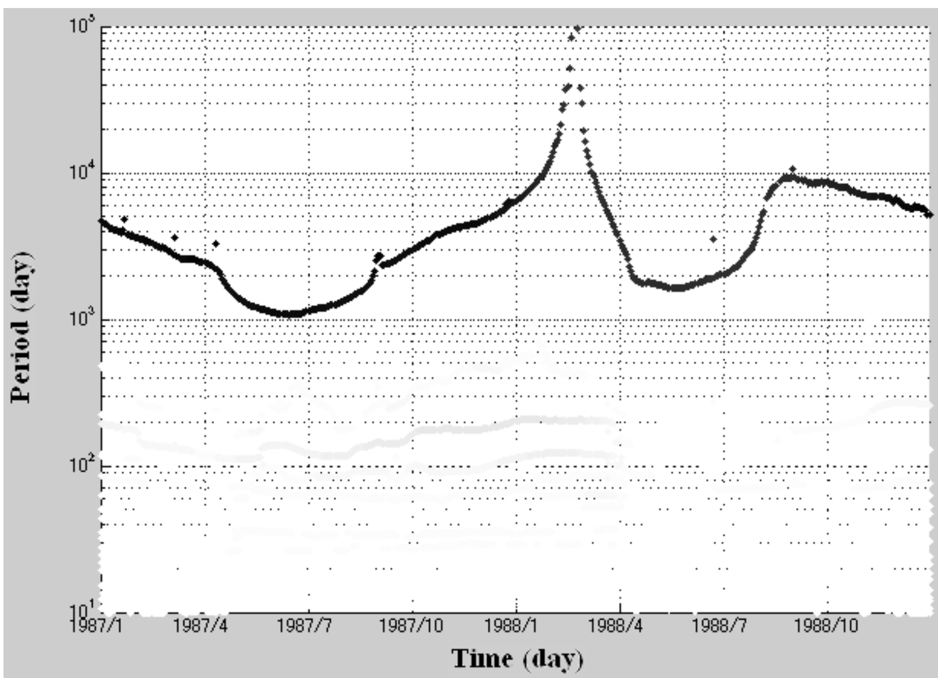

Figure 7: The longest period element during the 2 years from January 1, 1987 (window size 256).

10,000 days afterwards. Regarding the short period element, see Figure **8**, the period suddenly changes approximately in April, 1987 and April, 1988. During the period when a period suddenly changes, the change in the price ratio becomes particularly large.

When we consider the results of our analysis of the long period element with a window length of 512 days, see Figure **9**, we see the period becomes infinite in May, 1988 and is stable at other times. The short period element, shown in Figure **10**, experiences period changes in June and October, 1988; in October, in particular, the change is intense.

4.2. The Worldcom Case

The Worldcom case is a window dressing settlement that was discovered in June 2002 and led to bankruptcy on July 21, 2002. As shown in Figure **11**, stock prices have fallen in this period. It is thought that

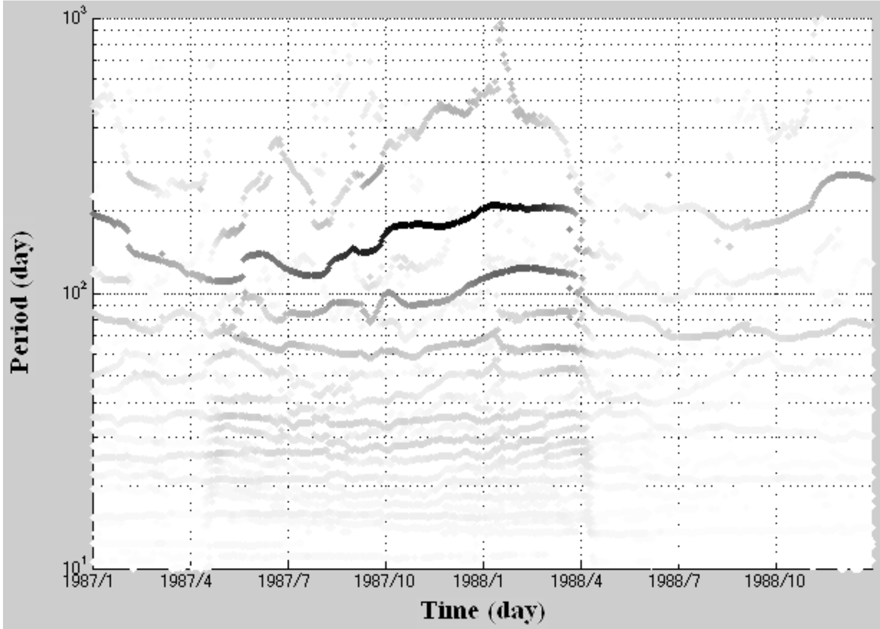

Figure 8: The shortest period elements during 2 years from January 1, 1987 (window size 256).

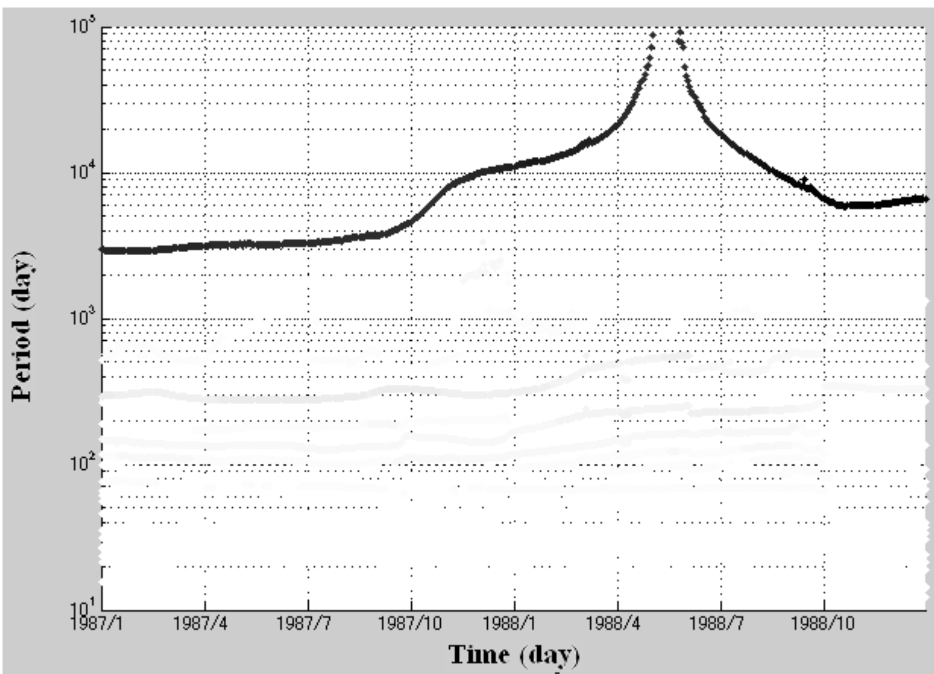

Figure 9: The longest period element during the 2 years from January 1, 1987 (window size 512).

as the Sept.11 attacks and the Enron case happened close to the time of the Worldcom case, they also influenced stock prices during the period. Therefore, we take results of our analysis for 2 years from July 2001, on the basis of these cases.

When we consider the results of the analysis of the long period element with a window length of 256 days, see Figure **12**, the phenomenon of a period tending to infinity can be confirmed by the example of November 2002. Regarding the short period element, as in Figure **13**, the period is generally ill-defined.

The relationship between the ratio of price changes and the time period can be confirmed.

The results of the analysis of the long period element with a window length of 512 days, shown in Figure **14**, show that the period becomes infinite for January 2003 to February 2003, but is stable at other

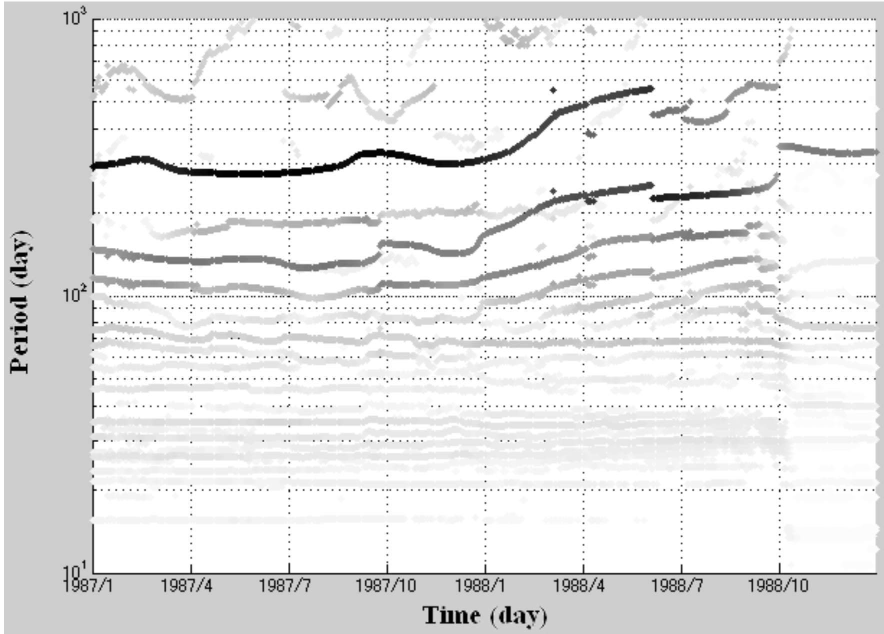

Figure 10: The shortest period elements during the 2 years from January 1, 1987 (window size 512).

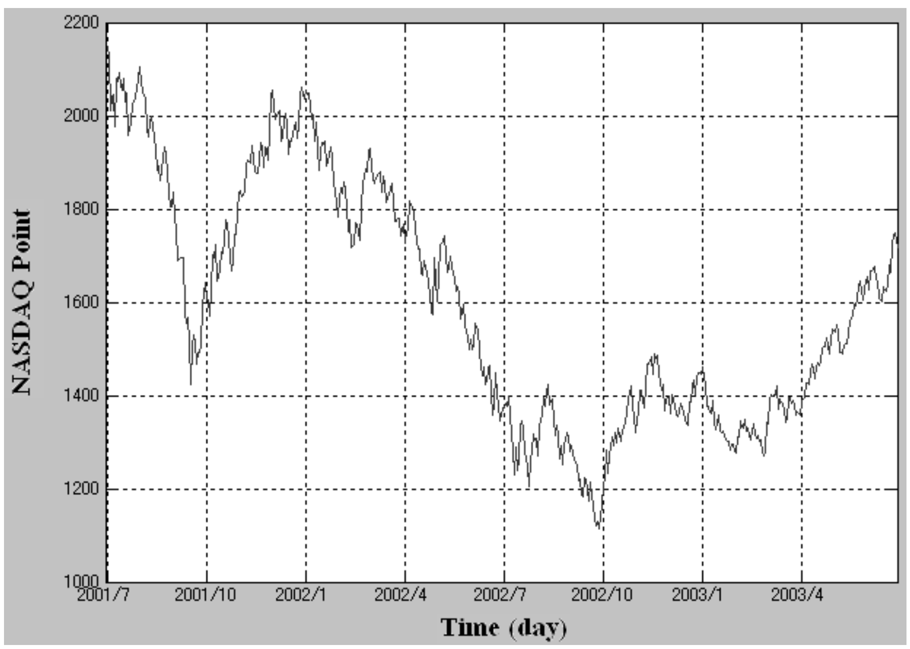

Figure 11: 2 years of the NASDAQ composite from July 1, 2001 (including the September 11 Attacks, Enron scandal, and WorldCom scandal).

points. Regarding the short period element, as in Figure **15**, the period is not as changeable as in the analysis results with a window length of 256 days, however, it fluctuates greatly from approximately October 2001 to July 2002.

4.3. The Lehman Shock

The Lehman Shock is the case of the Lehman Brothers was bankruptcy on September 15, 2008. The bankruptcy was the start of a global financial crisis involving the greatest aggregate amount of debt history. When we look at Figure **16**, we can see the stock prices slump from September 2008. The results of our analysis considering 2 years from January 2008 confirm what was occurring before and after this case.

The results of our analysis of the long period element with a window length of 256 days, as shown in Figure **17**, show that the period length tends to infinity in February 2009. Regarding the short period element,

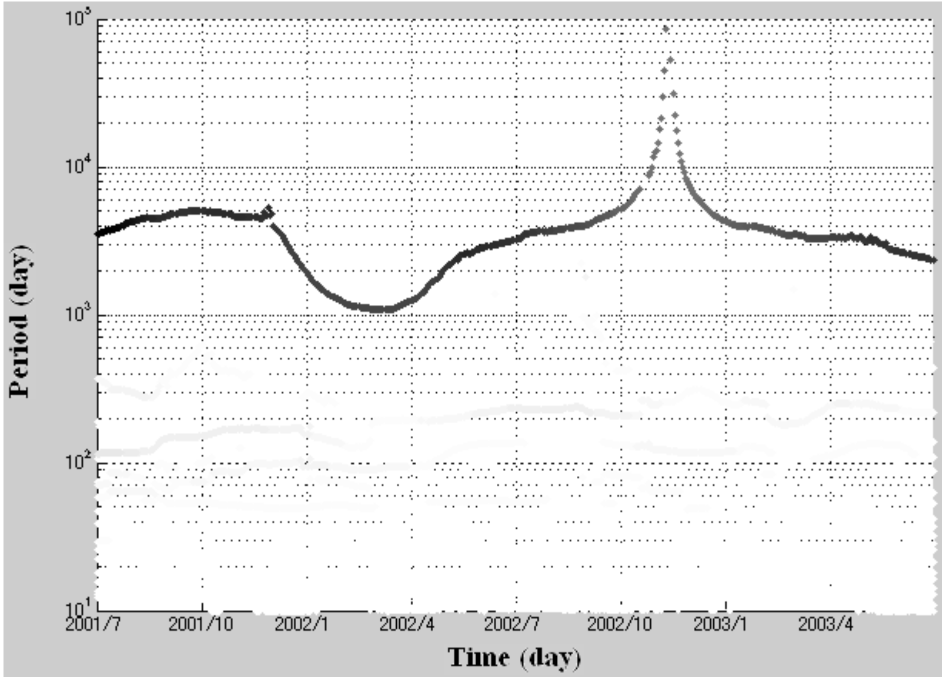

Figure 12: The longest period element during the 2 years from July 1, 2001 (window size 256).

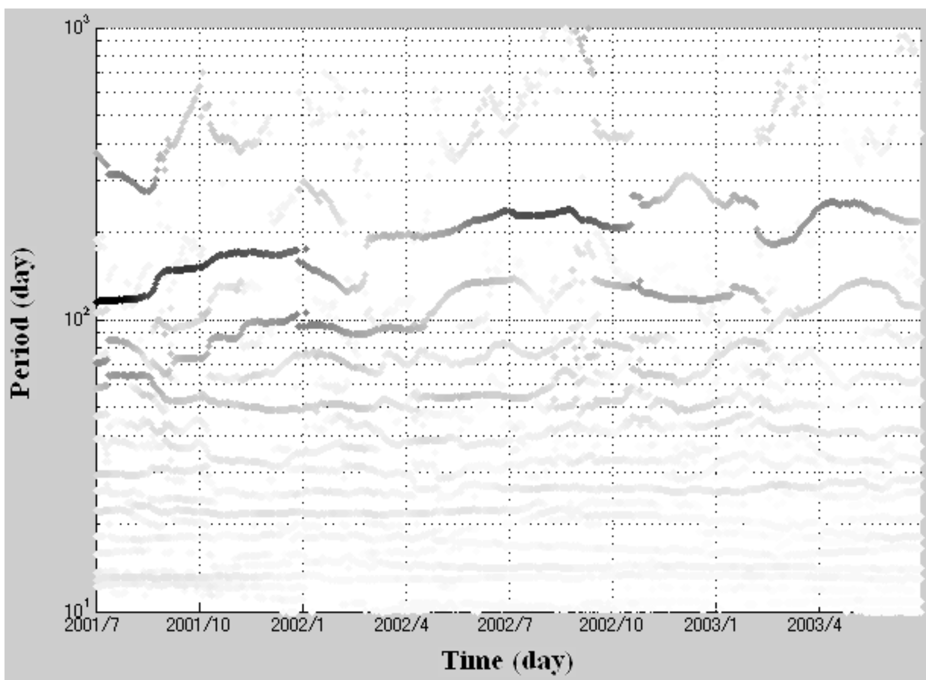

Figure 13: The shortest period elements during the 2 years from July 1, 2001 (window size 256).

as in Figure **18**, the price ratio constituted of the short period element becomes small after June 2009.

Considering the results of our analysis of the long period element with a window length of 512 days, as shown in Figure **19**, we can see the period becomes infinite in March 2009 and is stable at other points. Regarding the short period element, as in Figure **20**, there is not the characteristic change in the period, however, we can confirm that a change in the period including December, 2008 and October, 2009 does occur.

5. DISCUSSION

In sections 3 and 4, we have compared the periodic fluctuations given events that significantly influence stock prices. The period that fluctuates smoothly in the

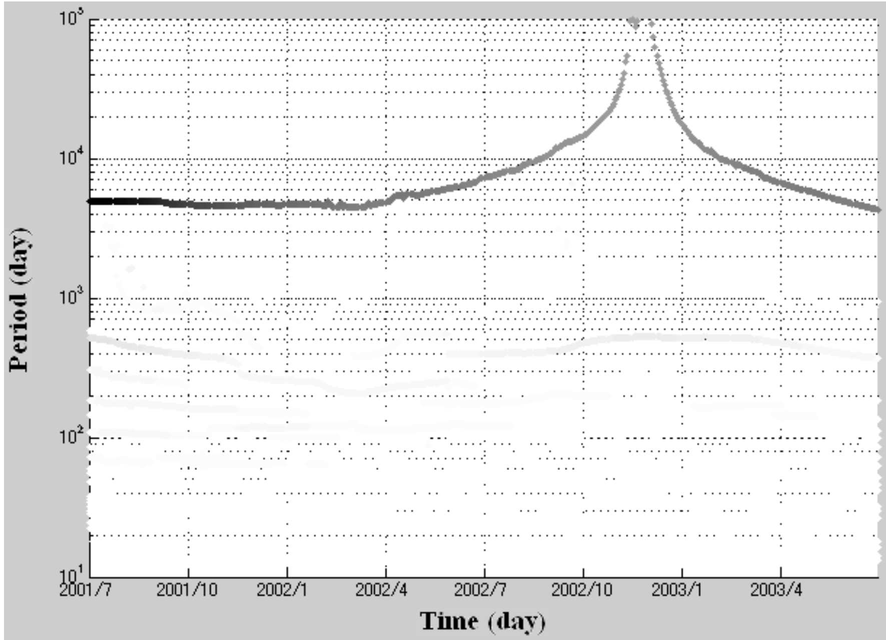

Figure 14: The longest period element during tje 2 years from July 1, 2001 (window size 512).

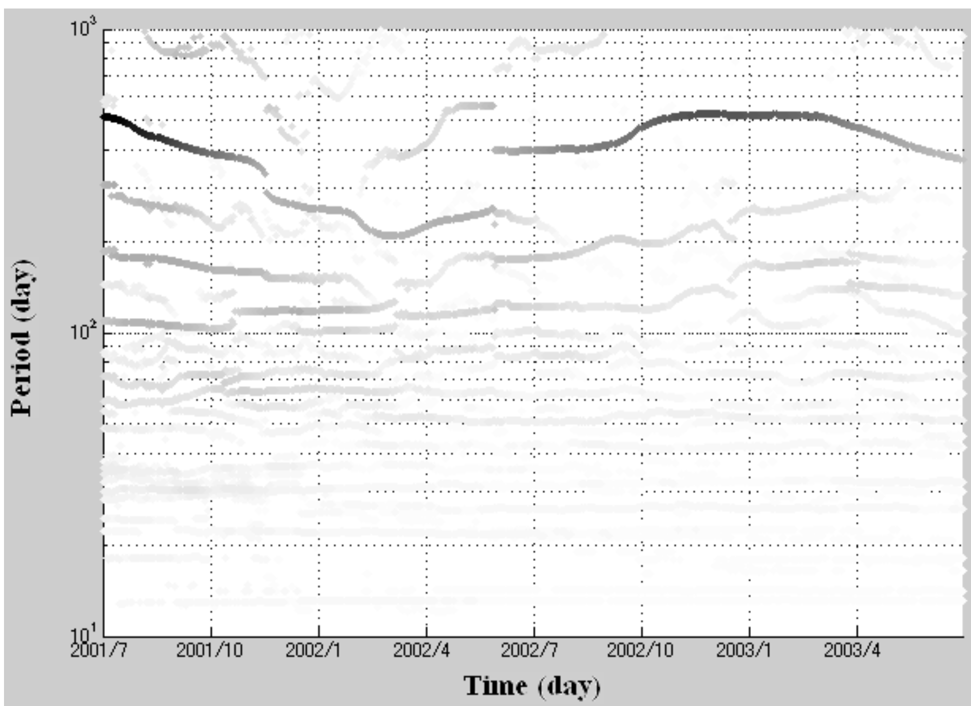

Figure 15: The shortest period elements during the 2 years from July 1, 2001 (window size 512).

approximate 24 years greatly fluctuates due to several events that occurred suddenly. For the long period element, the phenomenon that the period becomes infinite can be confirmed approximately 4-8 months after a sudden event occurred. The short period elements fluctuate smoothly for most of the time, however, there are intense fluctuations that occur in the same way as in the long period element, coinciding with several sudden events. This phenomenon conceivaly expresses the psychological situation of the markets, for example, the phenomenon of the market developing a panic and buying and selling is activity occurring accordingly.

The visualized periods correspond to in six periods of Elliott wave theory's ninth class, namely the Super-Cycle, Cycle, Primary, Intermediate, Minor, and Minute. The long period element varies from approximately

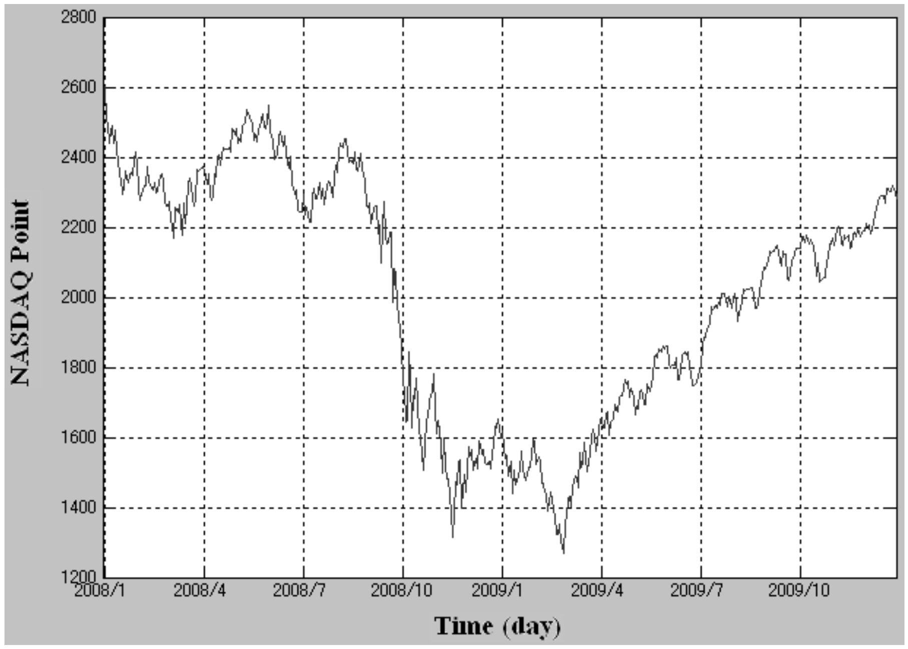

Figure 16: 2 years of theNASDAQ composite from January 1, 2008 (including the Lehman Shock).

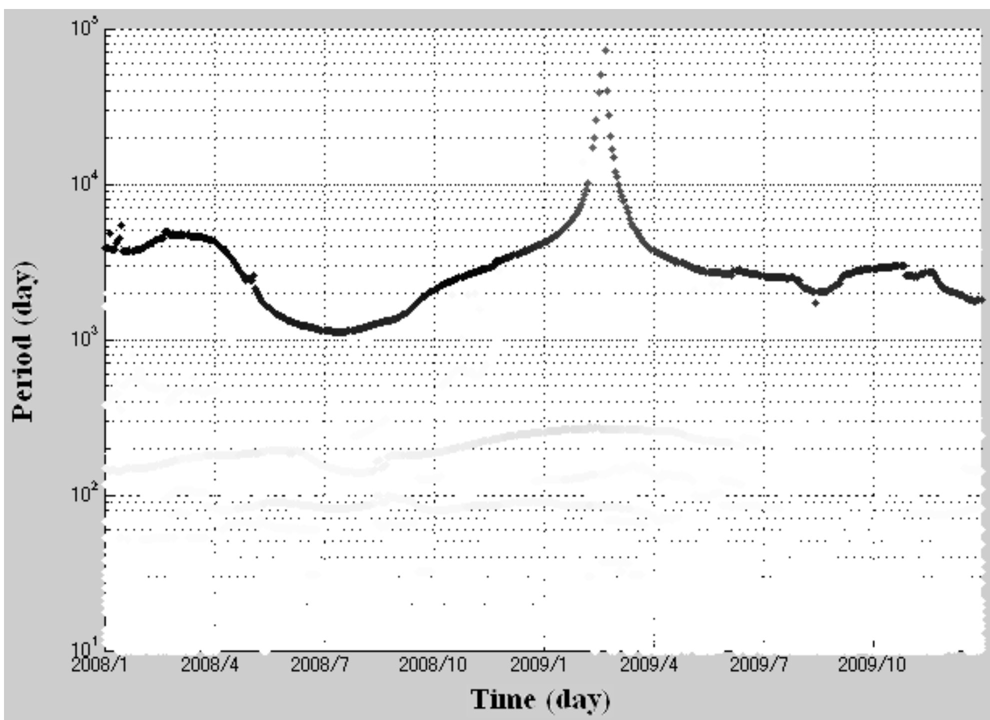

Figure 17: The longest period element during the 2 years from January 1, 2008 (window size 256).

1,000 days to 10,000 days, which is approximately 4 years to 40 years. Therefore, its results visualize the Super-Cycle and the Cycle of the Elliott wave theory, as shown in Table **1**. Likewise, the short period element varies from approximately 1 day to 1,000 days, that is from approximately 1 day to 2 years. Therefore, its results visualize the Primary and Minute periods, as shown in Table **1**. As we mentioned in subsection 2.2, in Elliott wave theory it is important to know the wave position in the present. In this experiment, if 6 class periods within the ninth class have been visualized, then predicting stock price might become easier than it has been to estimate them using experience and expectation.

Furthermore, the accurate visualization could solve the problem of it being difficult to estimate the cycle of

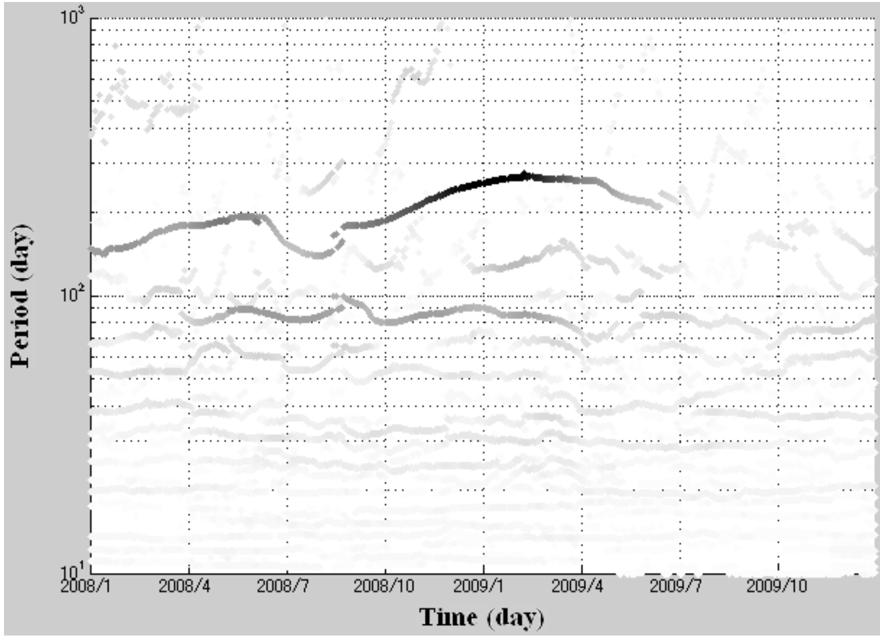

Figure 18: The shortest period elements during the 2 years from January 1, 2008 (window size 256).

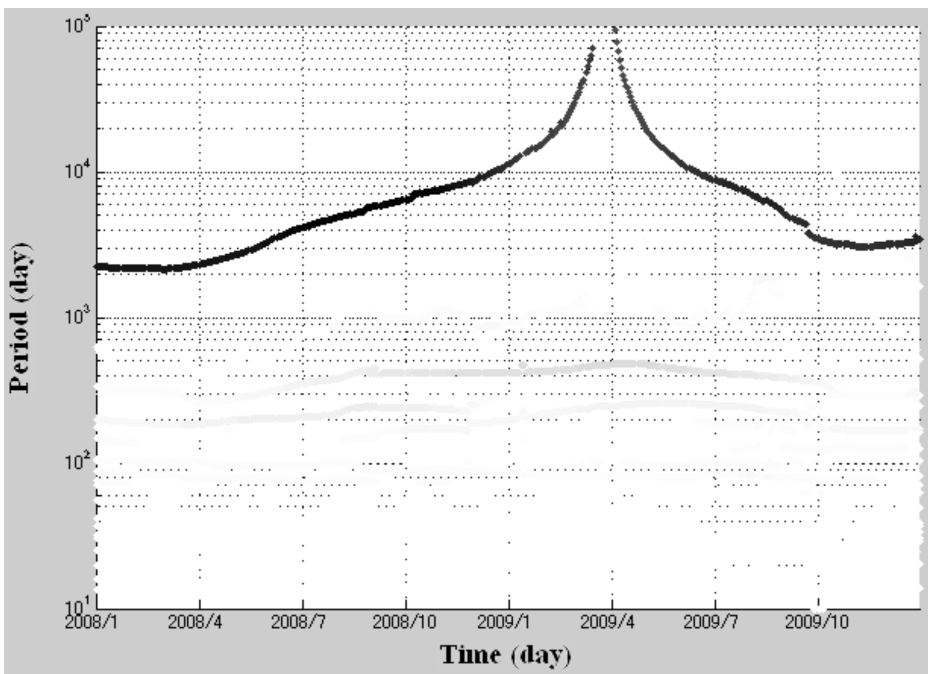

Figure 19: The longest period element during the 2 years from January 1, 2008 (window size 512).

stock prices. Meaning we can predict future values highly accurately.

Combining the methods used in this experiment and in previous works might mean we can predict the stock prices exactly.

6. CONCLUSION

In this paper, we have focused on the period of the stock prices, and we have developed a system to visualize the period of stock prices in time series, and to analyze it. As a result, we confirmed that the period of stock prices fluctuates in terms of time, and we discovered that many periods are part of the combination that constitutes stock price fluctuations. Moreover, we confirmed the price ratio of each period. In our research, we have used two window lengths, of 256 days and 512 days. The analysis results with the 256 day window length showed large fluctuations. On the other hand, the results with the 512 day window

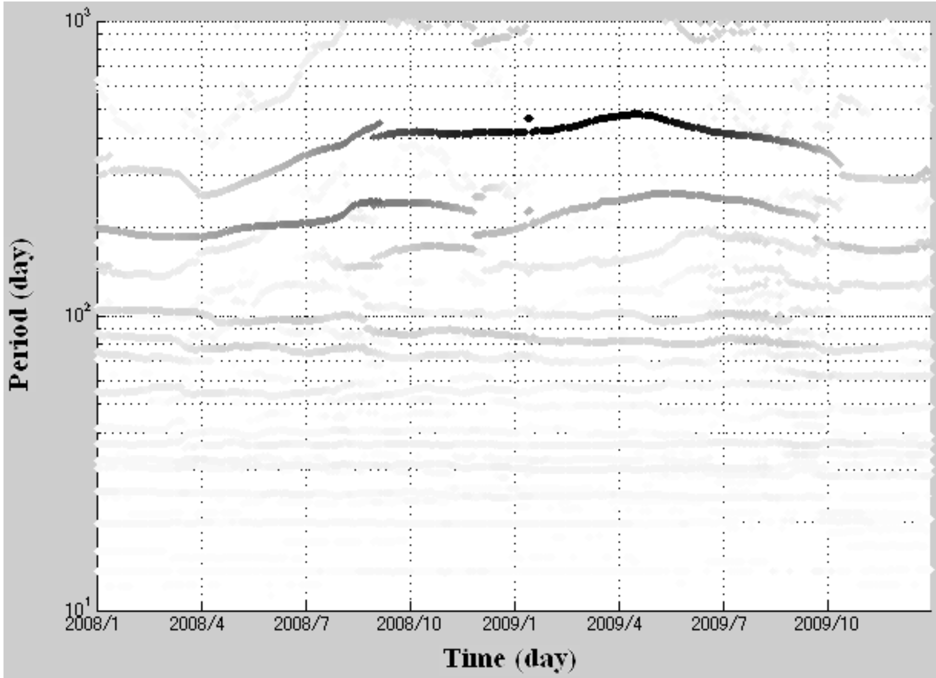

Figure 20: The longest period elements during the 2 years from January 1, 2008 (window size 512).

length showed the period was stable. In general, the period fluctuates gently. However, we confirmed that a large fluctuation occurs when a sudden significant event happens. In all our analysis results, the long period element increased four to eight months after a sudden event occurred. Likewise, for the short period element, we found that there was a large period fluctuation when a sudden event occurred. We confirmed that the cycle of the short period elements is changing from 10 days to 700 days, and it is having various length.

In the technical analysis, the change of moving average line represents the points of buying and selling.This change is named Golden Cross and Dead Cross, and this invest techniques is in general used for many short-term trading investors. There is no scientific evidence in these investment techniques, it is what most obtained empirically. Period fluctuation that has been visualized in this study is representing trend of stock market. Finding out a relationship between period elements and technical analysis indicator might give scientific evidence of their indicator.

Furthermore, a relation to Elliott wave theory is suggested because it is the periods applicable to the definition of this theory that have been visualized. If the present wave position of stock prices can be visualized, then estimating the movements of stock prices may become much easier.

In future study, using an Agent model, we will analyze which influences caused the large fluctuations in stock prices. In addition, we will consider and hopefully confirm that the periods fluctuate under whatever influence, by focusing on the index of technical analysis. Moreover, we will consider a system that combines this technique with conventional techniques, for example, we will check whether using data on periods as one of the indices in a Neural Network can improve its prediction accuracy.

Our work may lead to a significant result for the prediction of stock prices by adding the results of this experiment to various analysis techniques. We believe that a variety of analysis and knowledge of the nature of stock price fluctuations may well become a stepping stone towards the prediction ofstock prices.

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